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#USN: 1BM22CS259
import numpy as np
import random
import matplotlib.pyplot as plt

# Define the new objective function: f(x) = x * cos(x) - sin(2x)
def objective_function(x):
    return x * np.cos(x) - np.sin(2 * x)

# Particle Swarm Optimization (PSO) implementation
class Particle:
    def __init__(self, dimension, lower_bound, upper_bound):
        # Initialize the particle position and velocity randomly
        self.position = np.random.uniform(lower_bound, upper_bound, dimension)
        self.velocity = np.random.uniform(-1, 1, dimension)
        self.best_position = np.copy(self.position)
        self.best_value = objective_function(self.position[0])  # Evaluate first dimension

    def update_velocity(self, global_best_position, w, c1, c2):
        # Update the velocity of the particle
        r1 = np.random.rand(len(self.position))
        r2 = np.random.rand(len(self.position))

        # Inertia term
        inertia = w * self.velocity

        # Cognitive term (individual best)
        cognitive = c1 * r1 * (self.best_position - self.position)

        # Social term (global best)
        social = c2 * r2 * (global_best_position - self.position)

        # Update velocity
        self.velocity = inertia + cognitive + social

    def update_position(self, lower_bound, upper_bound):
        # Update the position of the particle
        self.position = self.position + self.velocity

        # Ensure the particle stays within the bounds
        self.position = np.clip(self.position, lower_bound, upper_bound)

    def evaluate(self):
        # Evaluate the fitness of the particle based on the objective function
        fitness = objective_function(self.position[0])  # Using only the first dimension for this 1D problem

        # Update the particle's best position if necessary
        if fitness < self.best_value:
            self.best_value = fitness
            self.best_position = np.copy(self.position)

def particle_swarm_optimization(dim, lower_bound, upper_bound, num_particles=30, max_iter=100, w=0.5, c1=1.5, c2=1.5):
    # Initialize particles
    particles = [Particle(dim, lower_bound, upper_bound) for _ in range(num_particles)]

    # Initialize the global best position and value
    global_best_position = particles[0].best_position
    global_best_value = particles[0].best_value

    # To track progress (fitness values over time and positions)
    fitness_history = []
    positions_history = []

    for i in range(max_iter):
        # Update each particle
        for particle in particles:
            particle.update_velocity(global_best_position, w, c1, c2)
            particle.update_position(lower_bound, upper_bound)
            particle.evaluate()

            # Update global best position if needed
            if particle.best_value < global_best_value:
                global_best_value = particle.best_value
                global_best_position = np.copy(particle.best_position)

        # Record the best fitness and particle positions for this iteration
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            fitness_history.append(global_best_value)
            positions_history.append([particle.position[0] for particle in particles])  # Store positions of particles (1D)

            # Optionally print the progress
            if (i + 1) % 10 == 0:
                print(f"Iteration {i + 1}/{max_iter} - Best Fitness: {global_best_value}")

        return global_best_position, global_best_value, fitness_history, positions_history

    # Plotting function for PSO progress
    def plot_pso_progress(fitness_history, positions_history, global_best_position, lower_bound, upper_bound, max_iter):
        # Plot Fitness Over Time
        plt.figure(figsize=(12, 6))

        plt.subplot(1, 2, 1)
        plt.plot(range(1, max_iter + 1), fitness_history, color='blue', label='Global Best Fitness')
        plt.title('Fitness Convergence Over Time')
        plt.xlabel('Iterations')
        plt.ylabel('Best Fitness Value')
        plt.grid(True)

        # Plot Particle Positions Over Time
        plt.subplot(1, 2, 2)
        for i in range(max_iter):
            plt.scatter(positions_history[i], [i] * len(positions_history[i]), color='blue', alpha=0.5, label=f'Iteration {i+1}' if i == 0 else "
        plt.scatter(global_best_position, max_iter, color='red', marker='X', label='Global Best Position')
        plt.title('Particle Positions Over Iterations')
        plt.xlabel('Position')
        plt.ylabel('Iteration')
        plt.grid(True)

        plt.tight_layout()
        plt.show()

    # Set the parameters for the PSO algorithm
    dim = 1                # One-dimensional problem
    lower_bound = -10      # Lower bound of the search space
    upper_bound = 10       # Upper bound of the search space
    num_particles = 30     # Number of particles in the swarm
    max_iter = 100         # Number of iterations

    # Run the PSO
    best_position, best_value, fitness_history, positions_history = particle_swarm_optimization(
        dim, lower_bound, upper_bound, num_particles, max_iter
    )

    # Output the best solution found
    print("\nBest Solution Found:")
    print("Position:", best_position)
    print("Fitness:", best_value)

    # Plot the progress of the PSO
    plot_pso_progress(fitness_history, positions_history, best_position, lower_bound, upper_bound, max_iter)
```

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Iteration 10/100 - Best Fitness: -9.8580439672337
Iteration 20/100 - Best Fitness: -9.85804488649004
Iteration 30/100 - Best Fitness: -9.858044886603542
Iteration 40/100 - Best Fitness: -9.858044886759474
Iteration 50/100 - Best Fitness: -9.858044886759485
Iteration 60/100 - Best Fitness: -9.858044886759487
Iteration 70/100 - Best Fitness: -9.858044886759487
Iteration 80/100 - Best Fitness: -9.858044886759487
Iteration 90/100 - Best Fitness: -9.858044886759487
Iteration 100/100 - Best Fitness: -9.858044886759487

Best Solution Found:
Position: [9.70257695]
Fitness: -9.858044886759487
```

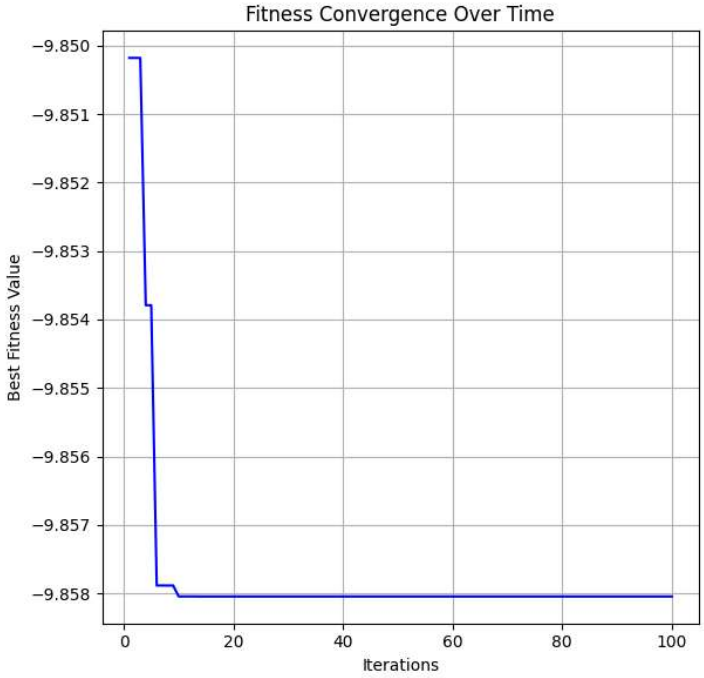

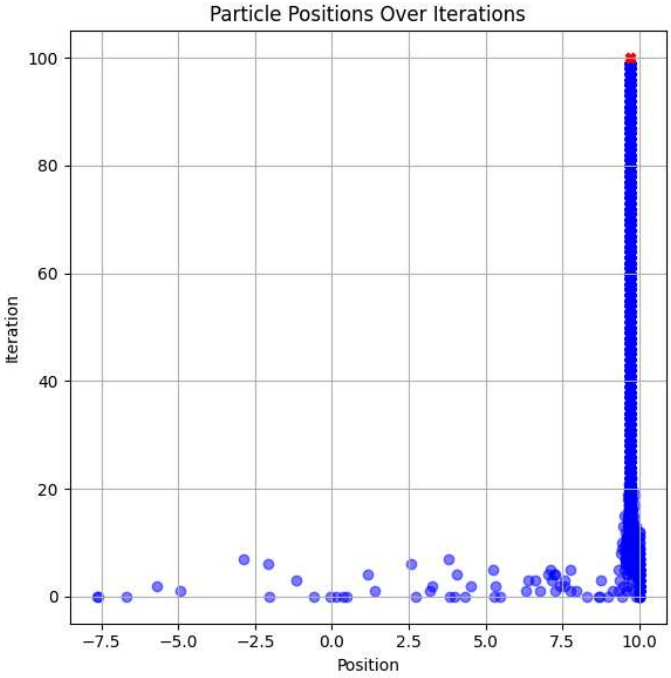


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#USN: 1BM22CS259
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import random

# Step 1: Define the objective function for portfolio optimization (Sharpe ratio)
def objective_function(weights, mean_returns, cov_matrix, risk_free_rate=0.02):
    """
    Objective function to calculate the negative Sharpe ratio for the portfolio.
    :param weights: Portfolio weights (array of length N)
    :param mean_returns: Expected returns of the assets (array of length N)
    :param cov_matrix: Covariance matrix of asset returns
    :param risk_free_rate: Risk-free rate (default 2%)
    :return: Negative Sharpe ratio (since PSO minimizes the objective function)
    """
    weights = np.array(weights)

    # Ensure no short-selling (weights between 0 and 1)
    weights = np.clip(weights, 0, 1)

    # Normalize the weights so they sum to 1, with a check to avoid division by zero
    weight_sum = np.sum(weights)
    if weight_sum == 0:  # If the sum of weights is zero, set them to be equal
        weights = np.ones_like(weights) / len(weights)  # Equal allocation
    else:
        weights = weights / weight_sum  # Normalize the weights

    # Calculate expected portfolio return and portfolio variance
    expected_return = np.dot(weights, mean_returns)
    portfolio_variance = np.dot(weights.T, np.dot(cov_matrix, weights))
    portfolio_volatility = np.sqrt(portfolio_variance)
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        portfolio_volatility = np.sqrt(portfolio_variance)

        # If volatility is 0 (no risk), we return a very large number (i.e., a very poor portfolio)
        if portfolio_volatility == 0:
            return np.inf

        # Calculate the Sharpe ratio: (return - risk-free rate) / volatility
        sharpe_ratio = (expected_return - risk_free_rate) / portfolio_volatility
        return -sharpe_ratio  # Minimize the negative Sharpe ratio

    # Step 2: Define the Particle class to represent a particle in the PSO algorithm
    class Particle:
        def __init__(self, dimension, lower_bound, upper_bound):
            """
            Initialize the particle with random position and velocity.
            :param dimension: Number of assets (dimension of the portfolio)
            :param lower_bound: Lower bound for asset allocation
            :param upper_bound: Upper bound for asset allocation
            """
            self.position = np.random.uniform(lower_bound, upper_bound, dimension)  # Random position (weights)
            self.velocity = np.random.uniform(-1, 1, dimension)  # Random velocity
            self.best_position = np.copy(self.position)  # Best known position for this particle
            self.best_value = np.inf  # Best value (objective function value, initially very high)

        def update_velocity(self, global_best_position, w, c1, c2):
            """
            Update particle velocity based on PSO update rule.
            :param global_best_position: Global best known position (optimal portfolio weights)
            :param w: Inertia weight
            :param c1: Cognitive coefficient
            :param c2: Social coefficient
            """
            r1 = np.random.rand(len(self.position))  # Random number for cognitive component
            r2 = np.random.rand(len(self.position))  # Random number for social component

            # Inertia: keeps the particle moving in its previous direction
            inertia = w * self.velocity

            # Cognitive component: pushes the particle towards its personal best position
            cognitive = c1 * r1 * (self.best_position - self.position)

            # Social component: pushes the particle towards the global best position
            social = c2 * r2 * (global_best_position - self.position)

            # Update velocity
            self.velocity = inertia + cognitive + social

        def update_position(self, lower_bound, upper_bound):
            """
            Update the particle's position (weights) based on its velocity.
            :param lower_bound: Lower bound for asset weights
            :param upper_bound: Upper bound for asset weights
            """
            self.position = self.position + self.velocity

            # Ensure the particle's position is within bounds (weights between 0 and 1)
            self.position = np.clip(self.position, lower_bound, upper_bound)

        def evaluate(self, mean_returns, cov_matrix, risk_free_rate):
            """
            Evaluate the fitness of the particle using the objective function.
            :param mean_returns: Expected returns of the assets
            :param cov_matrix: Covariance matrix of asset returns
            :param risk_free_rate: Risk-free rate for Sharpe ratio calculation
            """
            fitness = objective_function(self.position, mean_returns, cov_matrix, risk_free_rate)

            # Update the particle's best position if necessary
            if fitness < self.best_value:
                self.best_value = fitness
                self.best_position = np.copy(self.position)

    # Step 3: Define the PSO algorithm for portfolio optimization
    def particle_swarm_optimization(mean_returns, cov_matrix, num_particles=30, max_iter=100, w=0.7, c1=1.5, c2=1.5):
        """
        Main PSO function for portfolio optimization.
        :param mean_returns: Expected returns of the assets
        :param cov_matrix: Covariance matrix of asset returns
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        :param num_particles: Number of particles in the swarm
        :param max_iter: Number of iterations for the optimization
        :param w: Inertia weight
        :param c1: Cognitive coefficient
        :param c2: Social coefficient
        :return: Best portfolio weights, best Sharpe ratio, and fitness history
        """
        # Number of assets in the portfolio (dimension of the problem)
        dim = len(mean_returns)

        # Initialize particles
        particles = [Particle(dim, 0, 1) for _ in range(num_particles)]

        # Initialize the global best position and value
        global_best_position = particles[0].best_position
        global_best_value = particles[0].best_value

        fitness_history = []

        # Main optimization loop
        for i in range(max_iter):
            # Update each particle's velocity, position, and evaluate fitness
            for particle in particles:
                particle.update_velocity(global_best_position, w, c1, c2)
                particle.update_position(0, 1)
                particle.evaluate(mean_returns, cov_matrix, risk_free_rate=0.02)

                # Update global best if this particle has a better fitness value
                if particle.best_value < global_best_value:
                    global_best_value = particle.best_value
                    global_best_position = np.copy(particle.best_position)

            # Record the best Sharpe ratio at this iteration
            fitness_history.append(-global_best_value)  # The objective function is negative Sharpe ratio

            # Optionally, print progress every 10 iterations
            if (i + 1) % 10 == 0:
                print(f"Iteration {i + 1}/{max_iter} - Best Sharpe Ratio: {-global_best_value}")

        return global_best_position, -global_best_value, fitness_history

    # Step 4: Load the stock data and calculate returns and covariance matrix
    def load_stock_data(tickers, start_date, end_date):
        """
        Load stock data from Yahoo Finance and calculate returns and covariance matrix.
        :param tickers: List of stock symbols (e.g., ['AAPL', 'MSFT', 'GOOGL'])
        :param start_date: Start date for historical data (format: 'YYYY-MM-DD')
        :param end_date: End date for historical data (format: 'YYYY-MM-DD')
        :return: mean_returns (average returns) and cov_matrix (covariance matrix)
        """
        import yfinance as yf

        # Download stock data
        data = yf.download(tickers, start=start_date, end=end_date)['Adj Close']

        # Calculate daily returns
        returns = data.pct_change().dropna()

        # Calculate mean returns and covariance matrix
        mean_returns = returns.mean()
        cov_matrix = returns.cov()

        return mean_returns, cov_matrix

    # Step 5: Run the PSO optimization on stock data
    tickers = ['AAPL', 'MSFT', 'GOOGL', 'AMZN', 'TSLA']  # Example tickers
    start_date = '2020-01-01'
    end_date = '2023-01-01'

    # Load stock data and compute returns and covariance matrix
    mean_returns, cov_matrix = load_stock_data(tickers, start_date, end_date)

    # Run PSO to find optimal portfolio
    best_position, best_sharpe, fitness_history = particle_swarm_optimization(mean_returns, cov_matrix)

    # Step 6: Output the best portfolio weights and Sharpe ratio
    print("\nBest Portfolio Weights:")
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print(best_position)

print("Best Sharpe Ratio:", best_sharpe)
```

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[**********100%**********]  5 of 5 completed
Iteration 10/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 20/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 30/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 40/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 50/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 60/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 70/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 80/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 90/100 - Best Sharpe Ratio: -0.37461750264850174
Iteration 100/100 - Best Sharpe Ratio: -0.37461750264850174

Best Portfolio Weights:
[0. 0. 0. 0. 1.]
Best Sharpe Ratio: -0.37461750264850174
```